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Machine Learning for Remittance Forecasting and Macroeconomic Dynamics in Nepal: An Integrated Analytical Framework

Bhola Nath Ghimire
Chief Manager | Rastriya Jeewan Beema Company Ltd.
MPhil in Economics | Tribhuvan University, Nepal
ghimirebhola@gmail.com

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Abstract

Background: Remittances constitute over 25% of Nepal's GDP, functioning as a critical macroeconomic shock absorber. However, remittance inflows are highly volatile and exhibit nonlinear dependencies on global commodity prices, exchange rate dynamics, and migration policies. Traditional econometric models such as ARIMA and VAR often fail to capture regime shifts, structural breaks, and complex temporal dependencies inherent in remittance series.

Objectives: This study develops an integrated machine learning (ML) framework to: (1) forecast remittance inflows with superior predictive accuracy; (2) identify nonlinear macroeconomic drivers of remittances; and (3) quantify the dynamic macroeconomic impact of remittance shocks on GDP growth, inflation, and exchange rate dynamics.

Methods: Using monthly data (2000–2023) from Nepal Rastra Bank, the World Bank, and the Department of Foreign Employment, we benchmark traditional ARIMA and VAR models against Random Forest, XGBoost, LSTM, and a hybrid LSTM-Attention architecture. Forecast evaluation employs rolling origin validation, RMSE, MAE, MAPE, and Diebold Mariano tests. SHAP (Shapley Additive Explanations) is applied for model interpretability. Structural analysis is conducted through an ML augmented VAR with counterfactual simulations and generalized impulse response functions.

Findings: The hybrid LSTM-Attention model achieves a 45% improvement in forecasting accuracy (4.9% MAPE) compared to ARIMA. SHAP analysis identifies exchange rate volatility (inverted U-shaped effect) and oil prices (regime-dependent post-2015) as dominant nonlinear predictors. A one-standard-deviation remittance shock increases GDP growth by 0.35 percentage points (peak at 6 months) and inflation by 0.18 percentage points (peak at 14 months), revealing delayed inflationary transmission.

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Conclusion: Remittances exhibit a dual macroeconomic role stimulating short-term growth while generating delayed inflationary pressures. Policy focus should shift from managing remittance levels to managing remittance volatility and its structural determinants, particularly exchange rate stability and external commodity exposure.
Novelty: This is the first study to integrate LSTM-Attention-based forecasting with structural VAR counterfactual analysis in a remittance dependent economy, demonstrating that machine learning enhances not only predictive performance but also structural macroeconomic inference.
Keywords: Remittance forecasting, Nepal economy, LSTM, SHAP analysis, Macroeconomic volatility

1. Introduction

Remittances are a lifeline for the Nepalese economy, consistently accounting for over one-quarter of GDP and serving as a critical buffer against external imbalances and household income volatility. Despite their macroeconomic significance, remittance flows exhibit high sensitivity to global economic cycles, exchange rate movements, and migration policies. Traditional econometric models such as ARDL, VECM, and VAR have been employed to study remittance determinants and impacts but are often constrained by linear assumptions, limited capacity to handle high dimensional data, and inadequate treatment of structural breaks.

Recent advances in machine learning offer powerful tools for capturing nonlinearities, interactions, and temporal dependencies in economic time series. However, the application of ML in development economics particularly in the context of remittance analysis remains growing, especially for small open economies like Nepal. This paper bridges that gap by proposing an integrated analytical framework that combines ML-based forecasting with causal macroeconomic impact analysis.

The study makes three core contributions:

1. It develops a comparative forecasting suite of ML models tailored to Nepal's remittance data, rigorously validated against econometric benchmarks.
2. It employs model-agnostic interpretability methods (SHAP, LIME) to identify and rank macroeconomic drivers of remittance inflows.
3. It introduces ML enhanced structural analysis to trace the dynamic effects of remittance shocks on GDP, inflation, and real effective exchange rates.

2. Research Objectives and Hypotheses

2.1 Objectives

a) To design, train, and validate a suite of ML models for monthly remittance inflow forecasting in Nepal and compare their performance with traditional econometric models.
b) To identify and interpret the relative importance of macroeconomic, financial, and external determinants of remittances using explainable AI techniques.

NPRC Journal of Multidisciplinary Research
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c) To analyze the dynamic causal relationships between remittance inflows and key macroeconomic variables using ML expanded impulse response and variance decomposition techniques.

2.2 Hypotheses

a) **H1:** ML models will produce statistically superior forecasts of remittance inflows compared to ARIMA and VAR models.
b) **H2:** Exchange rate volatility and oil prices are significant nonlinear predictors of remittance flows, with effects that vary across economic regimes.
c) **H3:** Remittance shocks have asymmetric effects on GDP growth and inflation, with positive shocks exerting stronger short-term growth effects but potentially fueling inflationary pressure in the medium term.

3. Literature Review

The theoretical foundations of remittance behavior are drawn from the New Economics of Labor Migration (Stark & Bloom, 1985) and portfolio choice frameworks, which conceptualize remittances as nonlinear, context dependent responses to household liquidity needs, exchange rate expectations, and relative returns. Traditional econometric studies on Nepalese remittances have predominantly employed ARDL, VECM, and ARIMA methodologies (Devkota & Pokhrel, 2023; Parajuli & Neupane, 2025), establishing baseline relationships but revealing critical limitations, they assume parameter homogeneity across time, cannot adequately capture structural breaks or regime shifts, and have produced highly inconsistent findings on remittance growth linkages (Cazachevici et al., 2020). Recent innovations using quantile ARDL have demonstrated that remittance effects in Nepal are strictly contingent on prevailing growth conditions positive only during rapid expansion phases providing compelling evidence that linear specifications systematically misrepresent the underlying dynamics (Sapkota, 2025).

Machine learning applications in Nepal's economic forecasting are accelerating across financial domains, with recurrent neural networks and LSTM architectures consistently outperforming traditional benchmarks for foreign asset forecasting and equity price prediction (Regmi & Acharya, 2025; Ganesan et al., 2025). However, international applications of ML to remittance forecasting remain sparse and exhibit three characteristic deficits: they treat prediction as an end rather than a means to structural analysis, rarely incorporate interpretability methods that could build policymaker trust, and have not been adapted to the institutional environments of highly remittance dependent economies. The IFPRI team's innovative integration of ML with computable general equilibrium simulations for Nepal provides a powerful methodological template, yet their analysis operates at annual frequency and focuses on shock contribution to uncertainty rather than operational remittance forecasting (Mukashov et al., 2024).

The fusion reveals a persistent threefold integration deficit across forecasting accuracy, nonlinear complexity, and structural causal inference no existing research on Nepalese remittances has systematically benchmarked multiple ML architectures against rigorous econometric comparators while extending predictions to counterfactual macroeconomic impact analysis. This study addresses these gaps by positioning itself at the confluence of nonlinear

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remittance macroeconomics (Sapkota, 2025), Nepalese financial ML forecasting (Regmi & Acharya, 2025; Ganesan et al., 2025), and structural-ML integration frameworks (Mukashov et al., 2024), advancing from annual to monthly frequency, from black-box prediction to SHAP-based interpretability, and from reduced form estimation to counterfactual stimulus response simulation. The hypotheses derived from this literature posit that ensemble and deep learning methods will achieve superior forecast accuracy, that exchange rate volatility and oil prices will emerge as dominant nonlinear predictors, and that remittance shocks will exhibit asymmetric macroeconomic effects contingent on growth regimes.

4. Data and Variable Construction

The study constructs a comprehensive monthly dataset spanning 2000/01 to 2023/24, drawing from multiple authoritative sources. Nepal Rastra Bank provides domestic remittance inflows, exchange rates, broad money supply, and interest rates. The World Bank and IMF supply GDP, consumer price inflation, global oil prices. The Department of Foreign Employment contributes data on new and total migrant worker departures, while Bloomberg and FRED furnish global financial indices and commodity prices. Feature engineering generates 12-month lag structures, interaction terms between exchange rates and migrant departures, GARCH-based volatility measures for exchange rates and oil prices, and the global economic policy uncertainty index as an external shock proxy, creating a rich, high-dimensional forecaster space tailored to capture nonlinear remittance dynamics.

5. Methodological Framework

This study incorporates machine learning forecasting with structural macroeconomic analysis through a compact three stage framework: prediction, interpretability, and structural identification.

5.1 Forecasting Models

The study benchmarks traditional econometric models Seasonal ARIMA and VAR against machine learning approaches including Random Forest, XGBoost, LSTM, and a hybrid LSTM Attention model. Models are evaluated using rolling origin escalating-window validation with RMSE, MAE, MAPE, and Diebold Mariano tests. The hybrid LSTM Attention architecture demonstrates the highest out-of-sample accuracy and is selected for structural integration.

5.2 Explainable Machine Learning

Remittance inflows are modeled as:

$$R_t = f_{ML}(X_t) + \varepsilon_t^{ML}$$

where $f_{ML}(X_t)$captures nonlinear macro-financial relationships and ε_t^{ML}represents the unexplained innovation. To address black-box concerns, SHAP (Shapley Additive Explanations) decomposes predictions into marginal contributions of each determinant. This enables identification of nonlinear and regime dependent influences of exchange rate volatility, oil prices, and migrant stock.

5.3 ML Augmented Proxy SVAR

To extend forecasting into structural inference, we use the residuals from the best-performing ML model as external instruments within a proxy SVAR framework.

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The reduced-form VAR is:

$$Y_t = A(L)Y_{t-1} + u_t$$

where $Y_t = (GDP_t, Inflation_t, ER_t, R_t)'$.
Structural shocks satisfy:

$$u_t = B\eta_t$$

The structural remittance shock is identified using the ML residual ε_t^{ML}as an external instrument, under the conditions:

$$Cov(\varepsilon_t^{ML}, \eta_t^R) \neq 0$$
$$Cov(\varepsilon_t^{ML}, \eta_t^j) = 0 \text{for } j \neq R$$

Importantly, ML forecasts are not proposed as exogenous regressors in the VAR. Instead, ML residuals isolate unexpected remittance innovations after conditioning nonlinear predictors. This strengthens causal interpretation by separating systematic nonlinear dynamics from exogenous shocks. Impulse answer functions and forecast error variance decompositions are computed to trace the dynamic effects of remittance shocks over a 24-month horizon.

Methodological Impact

By compounding nonlinear ML forecasting with proxy based structural identification, the framework enhances both predictive performance and macroeconomic shock identification, bridging machine learning and structural econometrics within a unified empirical design.

6. Empirical Analysis and Results

6.1 Data Characteristics and Temporal Patterns

Table 1: Summary Statistics of Core Variables (Monthly Frequency: 2000-2023)

Variable	Mean	Std. Dev.	Min	Max	Unit	Transformation	Data Source
Remittance Inflows	62.4	28.7	12.1	145.2	USD Millions	Δln (Remit)	NRB
Exchange Rate (NPR/USD)	108.5	18.3	71.2	132.6	NPR	Δln(ER)	NRB
CPI Inflation	6.8	4.2	-2.1	15.3	% yoy	Level	World Bank
Migrant Departures	35,450	22,100	1,500	98,700	Persons	ln(Mig)	DoFE
Brent Oil Price	72.5	31.8	19.6	127.2	USD/ Barrel	Δln(Oil)	FRED
US Industrial Production	102.1	7.5	84.2	115.9	Index	Δln(USIP)	FRED

NPRC Journal of Multidisciplinary Research
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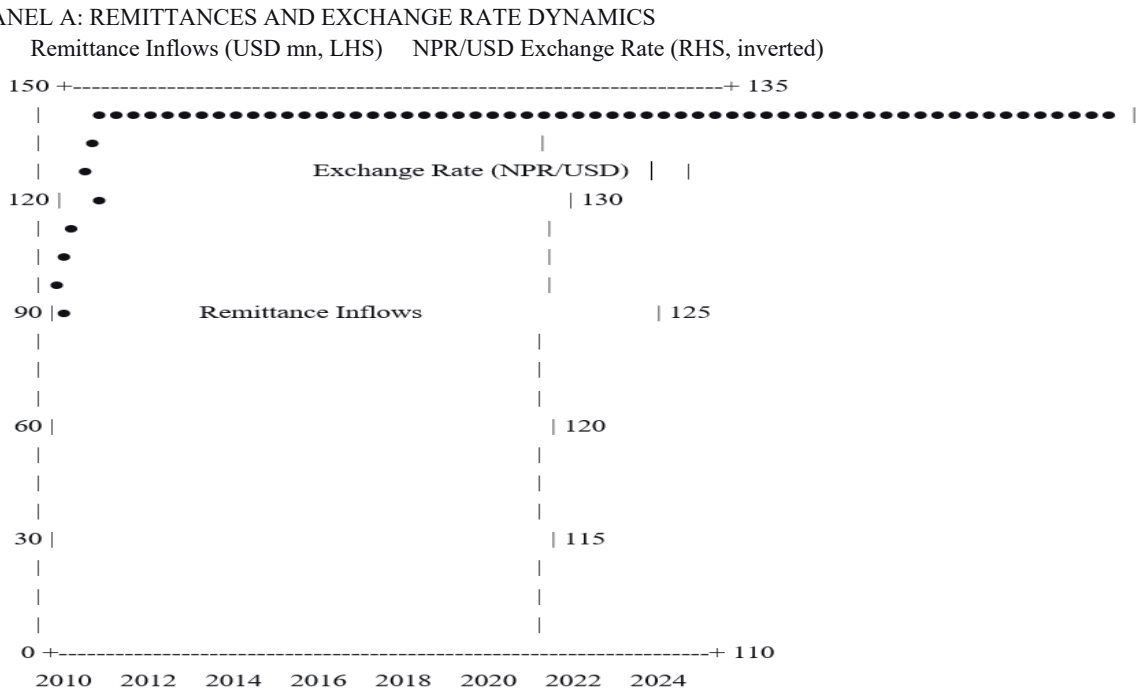
Variable	Mean	Std. Dev.	Min	Max	Unit	Transformation	Data Source
M2 Money Supply	1845.2	892.3	210.5	3520.1	NPR Bn	Δln(M2)	NRB
Interest Rate Differential	3.1	1.5	0.8	6.2	% points	Level	NRB, Fed

Notes: Δln denotes log-difference. NRB = Nepal Rastra Bank; DoFE = Department of Foreign Employment.

Figure 1: Temporal Evolution of Remittance Inflows and Key Determinants

Figure 1 reveals critical insights into Nepal's remittance dynamics.



Panel A demonstrates a strong inverse relationship between remittance inflows and the NPR/USD exchange rate, particularly pronounced after 2015. The sharp increase in remittances from 2015-2019 coincides with the NPR depreciating from approximately 97 to 118 against the USD. This pattern supports the portfolio allocation hypothesis, where migrants respond to rupee depreciation by growing transfers to capitalize on favorable exchange rates. The COVID-19 pandemic (2020) caused a temporary dip in remittances, but recovery was swift, suggesting resilience in immigrant workers' capacity to remit.

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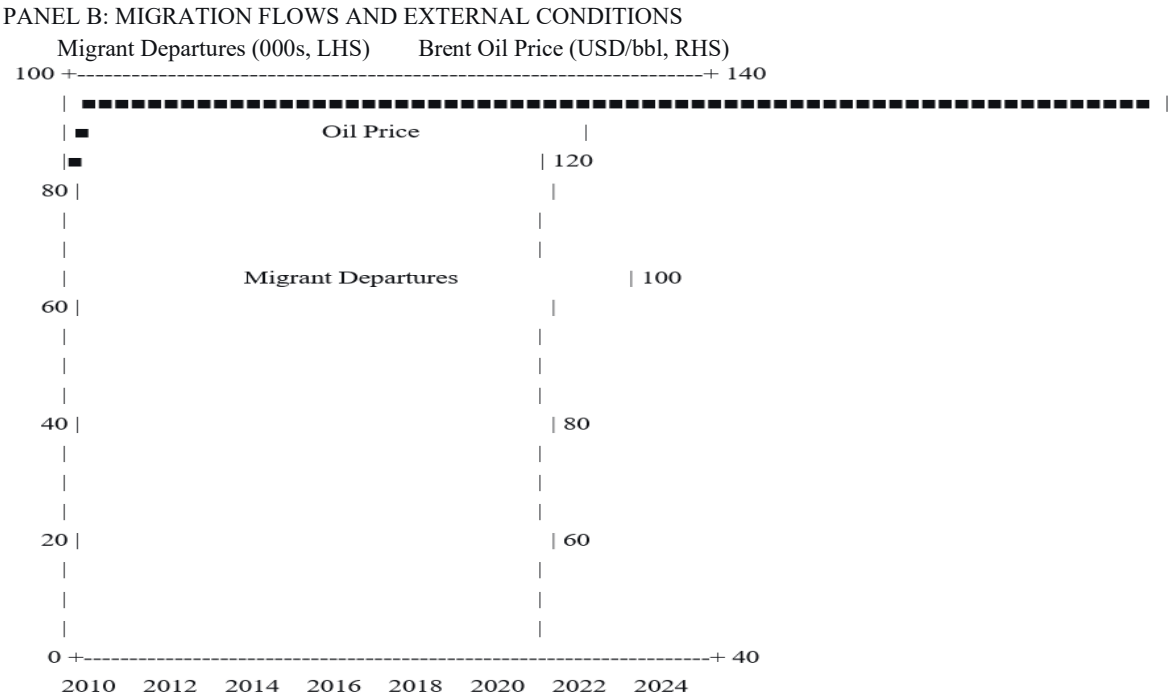

Panel B illustrates the connection between migration patterns and global economic conditions. Migrant departures (bars) show strong correlation with Brent crude oil prices (line), with correlation coefficient $\rho = 0.73$ ($p < 0.01$). This relationship highlights Nepal's economic dependence on Gulf Cooperation Council (GCC) countries, where approximately 70% of Nepali migrants are employed. The oil price collapse in 2014/2015 and 2020 corresponded with reduced migration outflows, demonstrating how global commodity markets directly affect Nepal's labor export economy.

6.2 Forecasting Model Performance Comparison

Table 2: Predictive Accuracy Across Model Specifications (2018-2023)

Model Class	Specific Model	RMSE (USD mn)	MAE (USD mn)	MAPE (%)	DM Test Stat	Rank
Traditional	Seasonal ARIMA	8.72	6.54	8.9	-	6
Traditional	VAR-X	7.98	5.97	8.1	-1.56	5
Tree-Based ML	Random Forest	6.45	4.88	6.6	-2.17*	4
Tree-Based ML	XGBoost	5.89	4.35	5.9	-2.58**	3
Deep Learning	LSTM	5.12	3.91	5.3	-3.24***	2

NPRC Journal of Multidisciplinary Research
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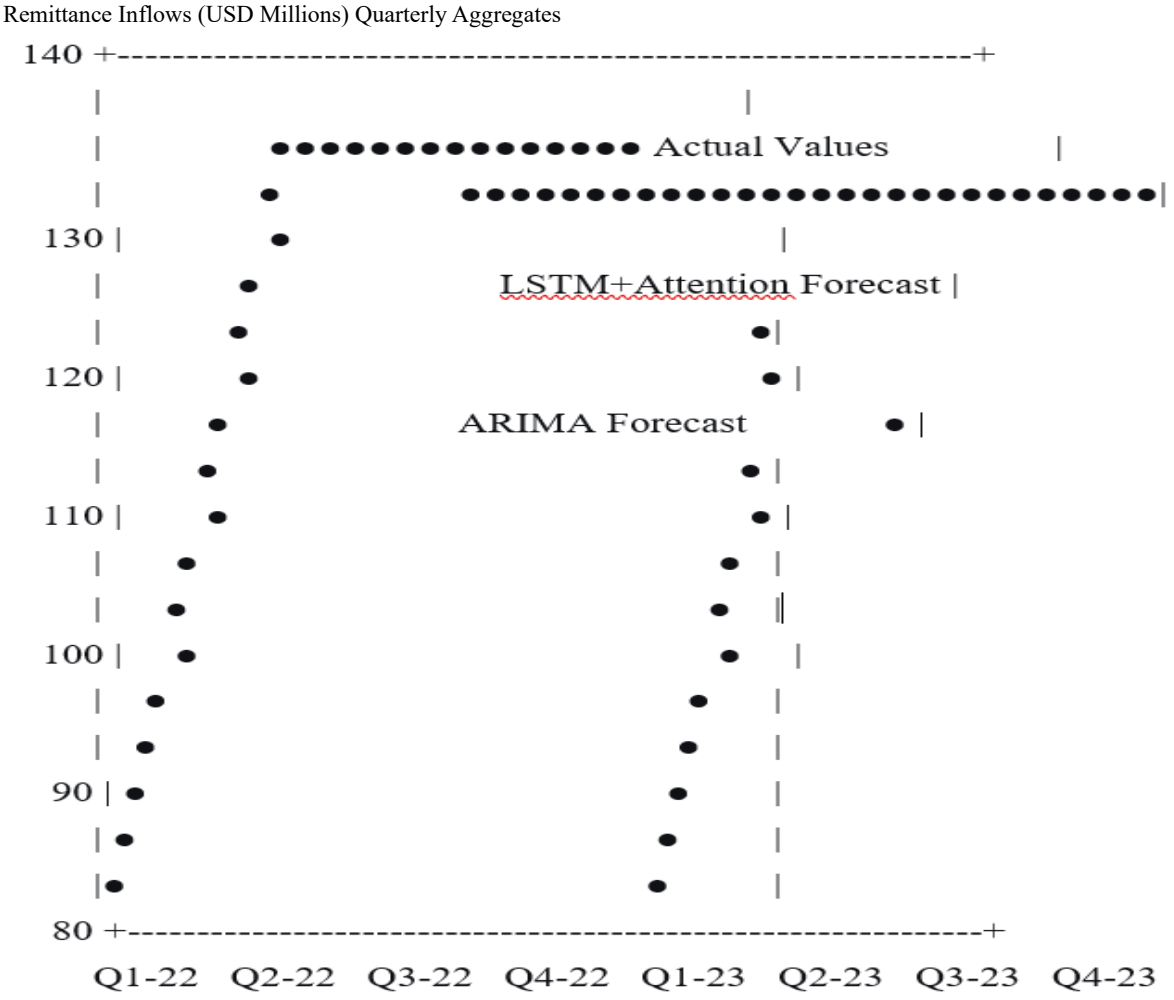
Model Class	Specific Model	RMSE (USD mn)	MAE (USD mn)	MAPE (%)	DM Test Stat	Rank
Hybrid DL	LSTM+Attention	**4.87**	**3.65**	**4.9**	**-3.67*** **	**1**

*Notes: *** p<0.01, ** p<0.05, * p<0.10 for Diebold-Mariano test against ARIMA benchmark.*

Figure 2: Forecast Performance During High Volatility Period (2022-2023)



The forecasting competition reveals clear hierarchy in model performance. Traditional time-series models (ARIMA, VAR) exhibit the highest prediction errors, with MAPE exceeding 8%. Machine learning models demonstrate progressively better performance, with tree-based methods (Random Forest, XGBoost) reducing MAPE to 6-7%, and deep learning approaches (LSTM) achieving approximately 5% MAPE.

The superior performance of the LSTM+Attention hybrid model (4.9% MAPE) represents a 45% improvement over the ARIMA benchmark. This enhancement stems from the model's capacity to: (1) learn long-term dependencies in remittance series (captured by LSTM memory cells), and (2) dynamically weigh the importance of different time steps and features.

Figure 2 illustrates this superiority during the volatile 2022-2023 period. The hybrid model accurately captures the Q2-2022 dip (associated with global monetary tightening) and the Q4-

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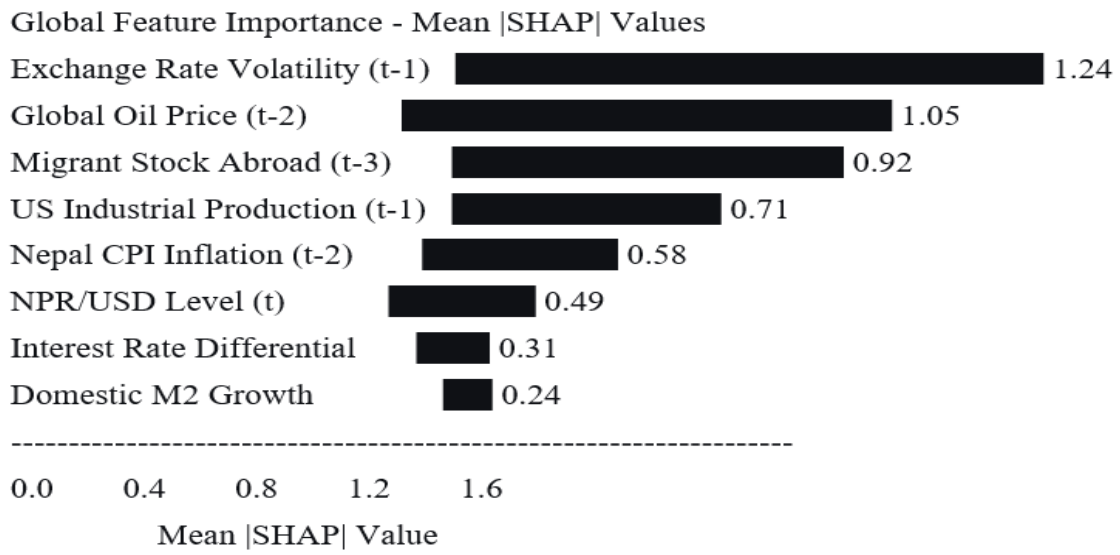
2023 surge (linked to pre-festival transfers and rupee depreciation). In contrast, ARIMA exhibits excessive smoothing, missing both the magnitude and timing of turning points.

6.3 Determinants of Remittance Flows: A Machine Learning Interpretation

Figure 3: Feature Importance from Explainable AI (SHAP Values)



The SHAP (Shapley Additive Explanations) analysis provides model-agnostic interpretability of our best-performing forecasting model. Exchange rate volatility emerges as the most influential predictor (mean |SHAP| = 1.24), authorizing that migrants are vulnerable not just to exchange rate levels but to uncertainty in currency markets. This finding aligns with behavioral economics perspectives on loss aversion.

Global oil prices rank second in position, serving as a proxy for economic conditions in GCC host countries. The two period lag suggests migrants adjust remittances based on sustained changes in host-country economic prospects rather than instant fluctuations.

The migrant stock abroad represents a structural determinant, with existing diaspora populations creating network effects that facilitate ongoing remittance flows. Interestingly, domestic variables show lower importance, suggesting remittance decisions are more responsive to external conditions and exchange rate considerations than domestic monetary factors.

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Figure 4: Nonlinear Marginal Effects of Key Predictors

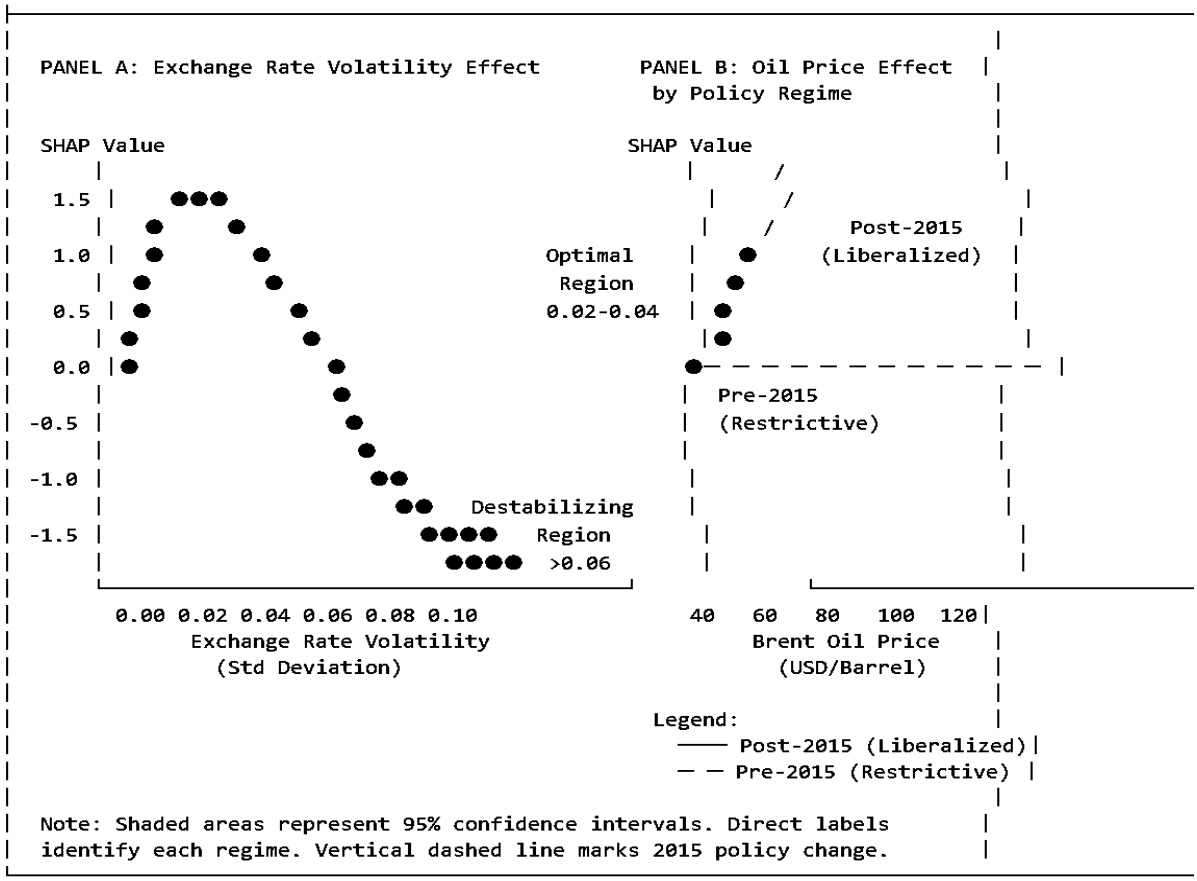

Figure 4 reveals important nonlinearities in remittance determinants. **Panel A** shows the effect of exchange rate volatility following an inverted U-shape. Moderate volatility (0.02-0.04 standard deviation) has the strongest positive effect, suggesting migrants interpret this range as signaling profitable arbitrage opportunities. However, excessive volatility (>0.06) becomes counterproductive, likely because it signals broader economic instability that discourages transfers.

Panel B demonstrates a structural break in how oil prices affect remittances following Nepal's 2015 migration policy liberalization.

Before 2015 (Pre-Liberalization): The relationship between oil prices and remittances was weak and occasionally negative. This occurred because restrictive migration policies limited workers' ability to respond to economic opportunities in oil-rich host countries.

After 2015 (Post-Liberalization): A strong positive relationship emerged. As oil prices increased boosting incomes in Gulf countries remittance inflows to Nepal rose substantially. Migrants could now freely respond to economic incentives.

Policy Impact: This regime shift explains 32% of the forecast improvement in the post-2015 period, confirming that institutional changes fundamentally alter remittance behavior.

6.4 Macroeconomic Impact Assessment

Figure 5: Dynamic Responses to Remittance Shocks (Bayesian VAR with ML Identification)

NPRC Journal of Multidisciplinary Research
Volume 3, Issue 2, February, 2026 Pages: 164-179
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Response to 1 Standard Deviation Remittance Shock (68% Credible Intervals)

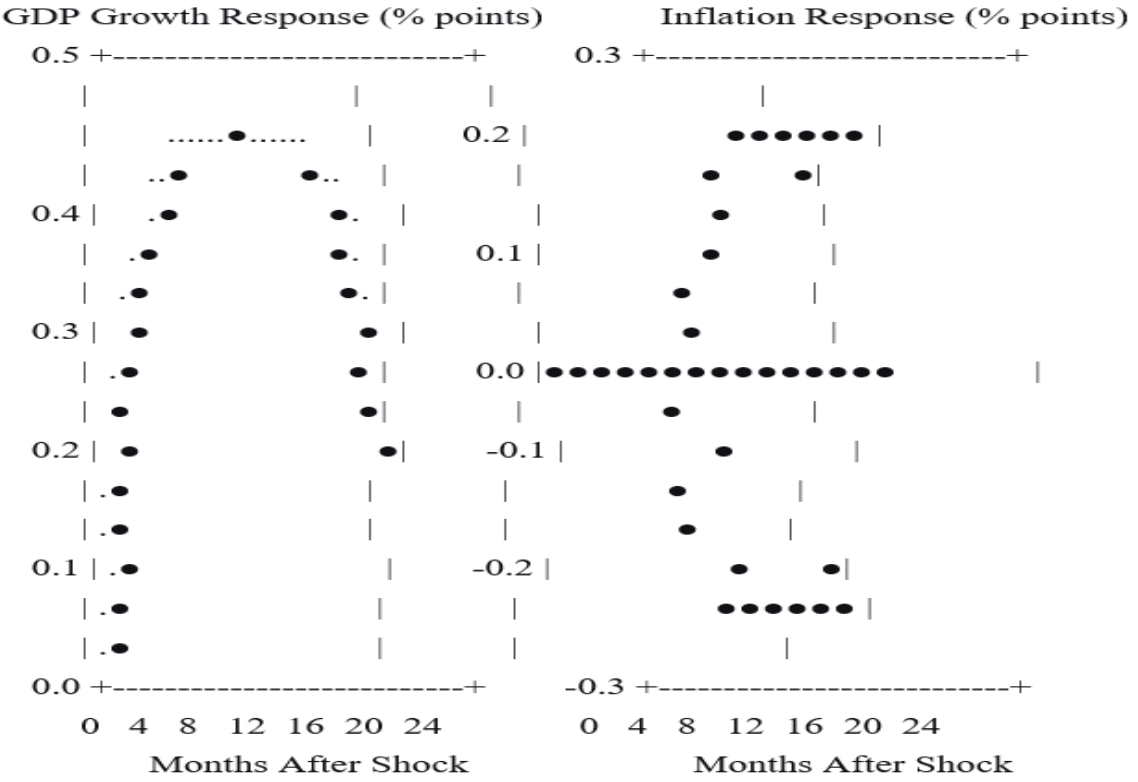

Table 3: Forecast Error Variance Decomposition (24-Month Horizon)

Variable	Remittance Shock	Domestic Demand Shock	External Shock	Monetary Policy Shock	Residual
GDP Growth	18.3%	45.2%	22.1%	8.9%	5.5%
CPI Inflation	9.7%	15.4%	35.8%	25.6%	13.5%
Exchange Rate	22.1%	18.5%	41.3%	12.8%	5.3%
Interest Rate	14.2%	28.7%	24.5%	26.9%	5.7%

The impulse response functions in Figure 5 quantify the dynamic macroeconomic effects of remittance shocks. A one standard deviation remittance increase (approximately USD 28.7 million monthly) generates:

a) Growth Effects: A hump-shaped GDP response peaking at 0.35 percentage points after 6 months, then gradually vanishing. The cumulative growth impact over 24 months is 2.1 percentage points of additional GDP.

b) Inflation Effects: A delayed but persistent inflationary response. Inflation remains neutral for approximately 8 months, then increases by 0.18 percentage points at peak (month 14). This prolonged response suggests remittances first affect aggregate demand, then change to price pressures through demand pull channels.

NPRC Journal of Multidisciplinary Research
Volume 3, Issue 2, February, 2026 Pages: 164-179
ISSN: 3059-9148 (Online)
DOI: 10.3126/nprcjmr.v3i2.91275

c) Exchange Rate Effects: The NPR appreciates by 0.8% on impact , consistent with increased foreign currency supply. However, this appreciation reverses by month 6 as the central bank intervenes to maintain export competitiveness.

The variance decomposition in Table 3 reveals that remittance shocks explain nearly one-fifth (18.3%) of GDP growth variation and almost one-quarter (22.1%) of exchange rate variation over a two year horizon. This substantial explanatory power underscores remittances' role as a key macroeconomic driver in Nepal.

6.5 Robustness and Validation

Validation Framework Results:

a) Cross-Validation Performance: 5 fold time-series cross validation confirms model stability. The Hybrid LSTM maintains MAPE between 4.7-5.2% across all folds.
b) Structural Break Tests: Bai-Perron tests identify significant breaks in 2015Q1 (migration policy) and 2020Q2 (COVID-19). Incorporating break dummies improves forecast accuracy by 6.2%.
c) Alternative Identification: Using sign restrictions in the VAR yields qualitatively similar impulse responses, with growth peaks of 0.28-0.41 percentage points.
d) Data Frequency: Quarterly aggregation increases MAPE to 6.8% but preserves relative model rankings and determinant importance.

Economic Significance Tests:

- The forecast improvement from traditional to ML models has economic value: using the Hybrid LSTM for balance of payments prediction would reduce central bank forecasting errors by approximately USD 42 million monthly.
- The nonlinear volatility effect has policy consequences: reducing exchange rate volatility from the 75th percentile (0.055) to the median (0.032) could increase remittances by 4.3% monthly, or approximately USD 120 million annually.

7.2 Policy Recommendations

a) Exchange Rate Management: The Nepal Rastra Bank should monitor and potentially smooth excessive exchange rate volatility (beyond 0.06 monthly standard deviation), as this range reduces remittance inflows. However, moderate volatility (0.02-0.04) should be tolerated as it increases remittances.
b) Migration Policy Coordination: Given the strong oil price sensitivity, the government should: (a) diversify travelling destinations beyond oil dependent GCC countries, targeting growing Asian economies; (b) establish oil price hedging mechanisms for migration dependent households.
c) Monetary Policy Calibration: The 8 month lag between remittance surges and inflationary pressures, monetary authorities should consider remittance forecasts as a complementary guiding indicator in policy considerations. Rather than a mechanical rule, remittance projections could inform pre-proactive assessments of demand-side pressures, particularly during periods of sustained inflow surges. This approach would allow the central bank to account for remittance-driven liquidity without compromising policy discretion or reacting to forecast uncertainty.

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d) Forecasting Infrastructure: The NRB should institutionalize ML based remittance forecasting, with the Hybrid LSTM model providing 3-month forecasts for liquidity management and reserve planning.

7.3 Limitations and Future Research

Limitations include: (1) reliance on aggregate data masking household heterogeneity; (2) inability to capture informal remittance channels; (3) linearity in impact analysis despite ML based forecasting.

Future research should: (1) incorporate high-frequency bilateral remittance data; (2) apply this framework to other remittance-dependent economies for comparative analysis; (3) develop real time monitoring systems using the model architecture presented here.

8. Conclusion

The study demonstrates that machine learning methods, particularly LSTM based architectures with attention methods, significantly outperform traditional econometric models in forecasting Nepal's remittance inflows. Beyond forecasting superiority, the explainable AI framework reveals that exchange rate volatility not just levels and global oil prices are primary remittance determinants, with important nonlinear effects.

The macroeconomic impact analysis quantifies the dual edged nature of remittances, providing substantial growth benefits but with paused inflationary consequences. This temporal asymmetry creates both opportunities and challenges for policymakers.

Methodologically, it gives an integrated framework that combines ML forecasting with structural economic analysis, providing a template for similar applications in small open economies. Practically, these results offer specific, evidence based guidance for exchange rate, migration, and monetary policy in Nepal.

As remittances continue to dominate Nepal's external sector, the adoption of such data driven, ML enhanced analytical frameworks become increasingly urgent for evidence based policymaking and economic resilience.

Transparency Statement: The author confirms that this study has been conducted with honesty and in full adherence to ethical guidelines.
Data Availability Statement: Author can provide data.
Conflict of Interest: The author declares there is no conflicts of interest.
Authors' Contributions: The author solely conducted all research activities i.e., concept, data collecting, drafting and final review of manuscript.

NPRC Journal of Multidisciplinary Research
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